Expert Systems With Applications 62 (2016) 32–43

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Detecting financial misstatements with fraud intention using multi-class cost-sensitive learning

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A R T I C L E I N F O

Article history:
Received 3 February 2016
Revised 12 April 2016
Accepted 9 June 2016
Available online 11 June 2016

Keywords:
Financial misstatement detection
Financial restatements
Fraud intention
Multi-class cost sensitive learning

A B S T R A C T

We develop multi-class financial misstatement detection models to detect misstatements with fraud intention. Hennes, Leone and Miller (2008) conducted a post-event analysis of financial restatements and classified restatements as intentional or unintentional. Using their results (along with non-misstated firms) in the form of a three-class target variable, we develop three multi-class classifiers, multinomial logistic regression, support vector machine, and Bayesian networks, as predictive tools to detect and classify misstatements according to the presence of fraud intention. To deal with class imbalance and asymmetric misclassification costs, we undertake cost-sensitive learning using MetaCost. We evaluate features from previous studies of detecting fraudulent intention and material misstatements. Features such as the short interest ratio and the firm-efficiency measure show discriminatory potential. The yearly and quarterly context-based feature set created further improves the performance of the classifiers.

1. Introduction

Can we detect accounting fraud? How are intentional financial misstatements different from accounting irregularities without managerial intent? Answering these questions is of critical importance to the efficient functioning of capital markets and to increase our understanding of financial statement fraud. Fraudulent financial statements affect not just shareholders, but also lenders, creditors and employees. Perols (2011) estimates the cost of financial statement fraud in the U.S. to be $572 billion per year.

Due to the significance of this topic, academics have performed post-event studies extensively to understand the causes, motivations, and consequences of financial misstatements and earnings manipulation (Beneish, 1999; Dechow, Ge, & Schrand, 2010; Dechow, Sloan, & Sweeney, 1995, 1996; DeFond & Jiambalvo, 1994; Ettredge, Scholz, Smith, & Sun, 2010; Gillett & Uddin, 2005; Hennes, Leone, & Miller, 2013; Jones, Krishnan, & Melendrez, 2008; Palmrose & Scholz, 2004; Schrand & Zechman, 2012). Building upon these studies, various prediction/detection models have been proposed in the accounting and data mining literature (Abbasi, Albrecht, Vance, & Hansen, 2012; Beneish, 1999; Cecchini, Aytug, Koehler, & Pathak, 2010; Dechow, Ge, Larson, & Sloan, 2011; Huang, Tsaih, & Yu, 2014; Kirkos, Spathis, & Manolopoulos, 2007; Kotsiantis, Koumanakos, Tzelepis, & Tampakas, 2006; Lin, Chiu, Huang, & Yen, 2015; Pai, Hsu, & Wang, 2011; Ragothaman, Carpenter, & Buttars, 1995).

To develop a detection/prediction model, databases which contain financial restatements, securities class action lawsuits, and financial regulatory investigation data, such as U.S. Securities and Exchange Commission (SEC) enforcement samples, have been used as a binary target variable. However, financial misstatements can be classified as involving either errors (i.e., unintentional misapplications of accounting rules) or irregularities (i.e., intentional misreporting). Previous studies often assume intentional misreporting either explicitly or implicitly, but the samples do contain both errors and irregularities (Beasley, 1996; Hennes, Leone, & Miller, 2008).

An intentional misstatement arises when management has incentives to manage earnings or commit fraud to meet certain objectives, such as maximizing personal gain through stock-based compensation (Erickson, Hanlon, & Maydew, 2006). When a restatement, the revision and publication of one or more of a company's previous financial statements with a material inaccuracy, is announced, investors show different responses depending on the presence of fraud intention. For example, Palmrose, Richardson, and Scholz (2004) report that the market reacts to restatement announcements differently showing an average abnormal return of −20% for financial restatements caused by deliberate

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http://dx.doi.org/10.1016/j.eswa.2016.06.016
0957-4174/

misreporting as opposed to an average abnormal return of −6% for non-fraud restatements. Also, when intentional misstatements are announced, a higher CEO/CFO turnover rate and more frequent securities class-action lawsuits follow compared to when unintentional restatements are announced (Hennes et al., 2008).

In comparison to intentional misstatements, unintentional misstatements are more likely to result from weak internal controls, to occur more frequently, to affect a broader range of accounts, and are likely to lead to auditor turnover (Hayes, 2014). Moreover, unintentional errors indicate either management is less reputed (Demerjian, Lev, Lewis, & McVay, 2012) or less incentivized to implement and maintain effective controls over financial reporting (Hayes, 2014).

Due to the difference between intentional and unintentional misstatements, researchers testing hypotheses involving managerial misconduct are at risk of making incorrect inferences regarding their hypotheses if they do not specifically distinguish intentional misstatements from unintentional errors (Hennes et al., 2008). This is especially critical given that the relative frequency of error-related misstatements has increased due to the tighter regulation in the post-Enron regulatory environment. Furthermore, if researchers limit their samples to only fraudulent misstatements for their detection models, they are underutilizing information by throwing away more commonly occurring unintentional misstatements. As a result, their models may not effectively detect more frequent but less egregious misstatements or discriminate between intentional misstatements and unintentional errors. We fill the void in the literature by distinguishing intentional financial misstatements from unintentional misstatements and by presenting a fraud-detection model.

To the best of our knowledge, our study is the first predictive study that classifies financial misstatements according to the presence of fraud intention using multi-class classifiers. Specifically, in this study, we investigate what causes intentional and material misstatements by classifying instances into three groups: 1. Intentional misstatement (Irregularity); 2. Unintentional misstatement (Error); and 3. No misstatement. To deal with asymmetric misclassification costs, we undertake cost-sensitive learning using MetaCost.

The contributions of this paper go further than filling a void in the literature by developing the first multi-class predictive models alone. Our study provides a quantitative tool to detect fraud intention of senior management of public firms. This should benefit academics and practitioners in financial regulation and capital markets. More specifically, regulators such as the SEC would benefit from our work because they could focus their investigation efforts on cases that are more likely to involve fraudulent intention. Also, investors and financial institutions would benefit from appropriately adjusting their levels of exposure to suspected firms in advance. Moreover, auditors can tailor their audit processes accordingly and minimize their possible legal risks.

In the following section, we review relevant literature. In Section 3, we describe the data used and the testing methodology employed. We then present the results in Section 4. Section 5 concludes this paper.

2. Financial misstatement literature

2.1. Fraud detection

West and Bhattacharya (2016) group common types of financial fraud into three groups: bank fraud (e.g. credit card fraud, Mortgage fraud, money laundering), corporate fraud (e.g. financial statement fraud, securities and commodities fraud) and insurance fraud (e.g. automobile insurance fraud, health card fraud). Researchers have analyzed various types of financial fraud (Bolton & Hand, 2002; Fawcett & Provost, 1997) and have proposed statistical and machine learning methods to detect fraud effectively (Ngai, Hu, Wong, Chen, & Sun, 2011; West & Bhattacharya, 2016). For example, Dal Pozzolo, Caelen, Le Borgne, Waterschoot, and Bontempi (2014) and Van Vlasselaer et al. (2015) propose credit card fraud detection models.

Among various types of financial fraud, Accounting researchers have performed post-event studies extensively to understand the causes, motivations, and consequences of financial statement fraud (Badertscher, 2011; Beasley, 1996; Beneish, 1999; Dechow et al., 1995, 1996; Erickson et al., 2006; Jones et al., 2008). As shown in Table 1, many of these post-event studies use the binary target variable made of fraud (misstatement) firms and non-fraud (non-misstatement) firms.

2.2. Classification of material misstatements according to fraudulent intention (post-event studies)

Researchers recently began to investigate and classify financial material misstatements according to management intent to mislead, manipulate or defraud, rather than to simply tag them all as examples of fraud. For example, Beasley (1996) searches Accounting and Auditing Enforcement Releases (AAERs) which as issued by the SEC during or at the conclusion of an investigation against a company, an auditor, or an officer for alleged accounting and/or auditing misconduct. He identifies fraud firms by removing AAERs not involving financial statement fraud (e.g., unintentional misapplication of GAAP).

In an award winning study, Hennes et al. (2008) formally propose the following three rules to classify financial restatements as errors (unintentional) or irregularities(intentional):

1. Classify any restatements using variants of the words “fraud” or “irregularity” in reference to the misstatement in 8-K filings as irregularities
2. Classify restatements with related SEC or Department of Justice investigations as irregularities
3. Presence or absence of other investigations into accounting matter (e.g., the audit committee hires a forensic accounting firm): classify restatements with related independent investigations as irregularities.

They perform three validity tests to support their classification approach. The first validity test shows a significant difference in the stock market reactions between the two groups: the mean (median) cumulative abnormal return for the unintentional-misstatement sample was 1.93%(0.90%) compared to 13.64%(19.4%) for the intentional-misstatement sample. The second validity test compares the frequency of securities class-action lawsuits, showing that 84 of the 105 intentional misstatements in their sample had contemporaneous class-action lawsuits while one of the 83 unintentional-misstatement samples had a related lawsuit. The third validity test shows that the percentage of restating firms experiencing CFO/CEO turnover in the 13 months surrounding the restatements (six months before to six months after) was 49%(64%) for CEOs(CFOs) in their intentional-misstatement sample but only 8%(12%) in the unintentional-misstatement sample. In the analysis for CFO/CEO turnover, they showed that the power of the hypotheses test on accounting restatements significantly improved either by limiting restatement samples to intentional misstatements or by including a control variable distinguishing unintentional misstatements from intentional misstatements. In a later study, Plumlee and Yohn (2010) classify financial restatements into four groups: intentional manipulation, internal company error, transaction complexity, and accounting standards.

Hayes (2014) proposes a simple text-search approach to classify financial restatements as unintentional errors or intentional